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Disequilibrium Econometrics on Micro Data

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This paper brings some empirical evidence to the construction of a more disaggregated view of disequilibrium. Individual data on firms collected by INSEE through periodic Business Surveys are used to construct the distribution of firms over the four possible disequilibrium regimes. Then the behavior of this distribution over time is analyzed by estimating dynamic conditional logit models on panel data.

The breakthrough paper on disequilibrium econometrics (Fair and Jaffee (1972)) is now more than ten years old. Quandt (1982) has recently surveyed the development of the econometric methods dealing with the particular non-linear models generated by fix-price models. Laffont (1983) has summarized and discussed the main estimation results of macro-disequilibrium models. Though these empirical results are interesting, they suffer from an excessive aggregation which prevents a sufficiently precise discussion of the nature of unemployment (classical unemployment vs. Keynesian unemployment) and of the appropriate corrective economic policies.

The purpose of this paper is to bring some empirical evidence to the construction of a more disaggregated view of disequilibrium by using individual data on firms collected by the Institut National de la Statistique et des Etudes Economiques (INSEE) through periodic Business Survey Tests.[1] A great potential of this more disaggregated approach is the ability to study the relative shares of classical and Keynesian unemployment. For policy purposes it is also important to explain why a given sector is in one type of unemployment or the other.

The paper is organized as follows. Section 1 presents the data and describes how the indicator of the regime in which a firm is can be constructed from the firm's answers to the INSEE surveys. The resulting distribution on the sample of firms over the four possible disequilibrium regimes is then discussed. Section 2 presents some general remarks on the estimation of conditional logit models on panel data as well as on the general form of the models that we propose to estimate. Section 3 studies the dynamics of the regime distribution by introducing the explanatory variables suggested by micro-disequilibrium models (see Muellbauer (1978), Malinvaud (1981), Kooiman (1982)). Section 4 concludes the paper.

1. DESCRIPTION OF DATA AND CONSTRUCTION OF VARIABLES

This section presents the data that are used in our empirical analysis.

1a. *Individual data*

Our micro data has been collected by INSEE from about 4000 firms through periodic Business Survey Tests.[2] These Survey Tests were taken three times a year (in June, November, and March) from June 74 to June 78, and four times a year (in June, October, January, and March) from June 78 to June 82. Only firms with a single major product are retained in the sample. Each firm was also classified according to the nature of its product into one of the following five sectors:

1. Agricultural and Food Industries,
2. Intermediate Goods,
3. Professional Equipment,
4. Automobile, Transportation,
5. Consumption Goods.

From the firm's answers to these surveys, two qualitative variables were constructed: (i) an indicator of surprise with respect to the demand received by the firm for its product,[3] and (ii) an indicator of the regime experienced by the firm during the period.

The demand surprise indicator, denoted MSD, is constructed from the answers to the following questions appearing in each survey:

"Indicate the probable change in demand for your product until the next survey: increasing, stable, decreasing."

"Indicate the change in demand for your product since the last survey: increasing, stable, decreasing."

From two successive surveys, we can readily define the variable MSD as:

$MSD = 1$ if the firm has over-evaluated its demand,

$MSD = 2$ if the firm has correctly evaluated its demand,

$MSD = 3$ if the firm has under-evaluated its demand.[4]

Let us now turn to the construction of the regime indicator IR. In the spirit of micro-disequilibrium models we are reasoning as if each firm has its local product market and its local labour market. Let IQ and IL be respectively the indicators of the states of the goods market and of the labour market, where:

$IL = 1$ if excess supply of labour,

$IL = 2$ if excess demand for labour,

$IQ = 1$ if excess supply of good,

$IQ = 2$ if excess demand for good.

Information on the indicators IQ and IL can be obtained from the INSEE surveys since in these surveys firms are asked questions about their perceived constraints on their product and labour markets. Specifically, the indicator IQ is obtained from the answer to the question:

"If you received more orders could you produce more with your actual means?"

If the firm answers YES we presume, following Malinvaud's remark (1980, p. 73), that the firm is constrained on its good market ($IQ = 1$), while if the firm answers NO we presume that the firm is not constrained on its good market ($IQ = 2$). Similarly, the indicator IL is obtained from the answer to the question:

"Do you now have difficulties in recruiting?"

If the firm answers YES, we presume that it is constrained on its labour market ($IL=2$), while if the firm answers NO we presume that it is not constrained on its labour market ($IL=1$).

There are obviously some problems with the interpretation to give to these answers; however, various alternative ways of using the answers to the INSEE surveys do not change the qualitative features of the empirical results presented in Section 3.[5]

Provided that a firm's answers to both of these questions are available it is possible to classify that firm in one of four possible disequilibrium regimes. Specifically,

$IR=1$ (Keynesian Unemployment) if $IQ=1$ and $IL=1$,

$IR=2$ (Under Consumption) if $IQ=1$ and $IL=2$,

$IR=3$ (Classical Unemployment) if $IQ=2$ and $IL=1$,

$IR=4$ (Repressed Inflation) if $IQ=2$ and $IL=2$.

According to this definition of the regime indicator we obtain Table I, which presents for the whole sample the distribution of the firms over the four possible disequilibrium regimes. These results can be compared with the *ex post* probabilities of the different regimes obtained by Artus, Laroque, and Michel (1984). One major feature of their

TABLE I

All five sectors

Date	Sample	Keynesian unemployment (%)	Under consumption (%)	Classical unemployment (%)	Repressed inflation (%)
75 03	1741	67·03	15·51	11·77	5·69
75 06	1818	69·70	15·51	9·79	5·00
75 11	1869	68·27	14·87	11·40	5·46
76 03	1842	62·81	18·24	11·67	7·28
76 06	1787	51·82	22·50	13·43	12·25
76 11	1829	55·28	20·78	13·72	10·22
77 03	1923	57·88	18·82	14·30	9·00
77 06	1917	58·53	18·62	14·45	8·40
77 11	2119	60·97	18·12	13·07	7·84
78 03	2013	62·49	18·33	12·57	6·61
78 06	2031	59·87	18·07	14·33	7·73
78 10	1785	60·62	17·54	14·73	7·11
79 01	2036	60·95	16·85	15·28	6·92
79 03	1988	60·82	15·79	16·35	7·04
79 06	1965	56·69	15·98	18·73	8·60
79 10	1996	54·61	16·33	20·14	8·92
80 01	1919	56·70	16·21	18·86	8·23
80 03	2031	54·01	16·45	20·38	9·16
80 06	1957	56·11	16·09	18·65	9·15
80 10	2015	63·23	16·63	14·14	6·00
81 01	1804	69·01	14·63	12·42	3·94
81 03	1726	71·55	12·57	12·34	3·54
81 06	1671	73·55	11·19	11·85	3·41
81 10	1774	70·97	12·63	12·91	3·49
82 01	1832	70·69	11·68	13·37	4·26
82 03	1743	69·31	13·42	12·79	4·48
82 06	1648	63·96	15·53	14·93	5·58

results is obtained here: namely, the predominance of the Keynesian unemployment regime.[6]

It would be interesting to comment in detail on Table I in the light of the French experience over the period 1975–1982. We shall only mention two important attempts that were made during this period to decrease unemployment with usual Keynesian policies: the Chirac experiment from June 1975 to June 1976 and the Mauroy experiment from June 1981 to June 1982. Both share the same features: a strong decline in the proportion of firms in the Keynesian unemployment regime with an increase in all other regimes. The Mauroy experiment appears less effective with a stronger relative increase in the proportion of firms in the classical unemployment regime. This is not surprising given that in the Mauroy experiment the low real wages have been increased substantially. Note also the dynamics after the Chirac experiment. The proportion of firms in the Keynesian unemployment regime increases again, but the proportion of firms in the classical unemployment regime continues to increase. Finally, the substantial increase in Keynesian unemployment from June 1980 to January 1981 seems to be due to the second oil crisis.

The same classification was carried out for each sector of the economy. In particular we found that the intermediate goods sector and professional equipment sector are the slowest to react; the automobile and transportation sector reacts quite strongly and rapidly; the consumption good sector reacts quickly but not as strongly.

1b. *Macro data*

Some macroeconomic variables are used as additional explanatory variables (see Muellbauer (1978), Malinvaud (1981), and Kooiman (1982)). All the macroeconomic variables were dichotomized and constructed from appropriate series obtained from the Comptes Nationaux Trimestriels published by INSEE for the period under study. If IX denotes the dichotomous variable associated with the latent continuous variable X, then the dichotomization rule is:

$$IX = 1 \quad \text{if } X \text{ is above a trend,}$$
$$IX = 2 \quad \text{if } X \text{ is below a trend,}$$

where the trend is obtained by adjusting a line on the time series X.

Two sectoral indicators and two national indicators were constructed in this way. These are:

- IGS: indicator of sectoral public expenditures,
- IGT: indicator of total public expenditures,
- ISB: indicator of the sectoral real cost of labour as measured by real gross wages, which include employer and employee social security payments and the like,
- ISN: indicator of purchasing power as measured by real take-home pay, which includes personal income taxes for the whole economy.[7]

In addition, lags of these indicators are also used as explanatory variables. Specifically, if IX is an indicator, then

$IX1$ is the indicator lagged 3 months,

$IX2$ is the indicator lagged 6 months,

$IX3$ is the indicator lagged 9 months.

2. ESTIMATION OF DYNAMIC CONDITIONAL MODELS ON PANEL DATA

All the models that we estimate are conditional logit models (see e.g. McFadden (1974), Nerlove and Press (1973, 1976)) where the endogeneous variable is the disequilibrium regime indicator IR. As a matter of fact, we consider a special case of the conditional logit model since all our explanatory variables are qualitative.

All our models are dynamic in the sense that they all include the 3 months lagged regime indicator $IR1$ as an explanatory variable. Thus we can think of the remaining explanatory variables as explaining the 3 months transition probability from one regime to another. Our models are therefore of the form:

$$IR|IR1, IA, IB, \ldots$$

where $IA, IB, \ldots$ are explanatory variables to be defined in Section 3. The parameterization used is the ANOVA parameterization (see Nerlove and Press (1976), Vuong (1982)). As usual we restrict the effect of each explanatory variable to its bivariate effect. Specifically, let $IR_{it}, IA_{it}, IB_{it}, \ldots$ denote the regime and the explanatory variables for the i-th firm at time t respectively. Let $KR, KA, KB, \ldots$ denote the number of categories of these variables where, in our case, KR is equal to 4, KA and KB are equal to either two or three. Then we have:

$$\begin{aligned} \log \Pr(IR_{it} = k | IR1_{it}, IA_{it}, IB_{it}, \ldots) = \mu + \alpha_k &+ \textstyle\sum_{l=1}^{KR} \beta_{k,l} D_l(IR1_{it}) \\ &+ \textstyle\sum_{a=1}^{KA} \beta_{k,a} D_a(IA_{it}) \\ &+ \textstyle\sum_{b=1}^{KB} \beta_{k,b} D_b(IB_{it}) + \cdots \end{aligned} \tag{1}$$

where $D_x(IX_{it})$ is equal to one if $IX_{it} = x$, and zero otherwise, the parameters α and β satisfy the ANOVA constraints:

$$\begin{aligned} &\textstyle\sum_{k=1}^{KR} \alpha_k = 0, \\ &\textstyle\sum_{k=1}^{KR} \beta_{k,x} = \sum_{x=1}^{KX} \beta_{k,x} = 0, \qquad \forall x, \forall k, \end{aligned} \tag{2}$$

and μ is a normalizing parameter depending only on the α's and β's so that, given $IR1_{it}$, IA_{it}, $IB_{it}, \ldots$, the conditional probabilities in (1) add up to one.[8]

Conditional logit models have been in general estimated on cross-section data only. The reason is that estimation of such models relies on the usual assumption that the observations are mutually independent, an assumption that is hardly justified in time series or panel data. Since we are ultimately interested in the effects of macro indicators such as IGT that therefore do not vary across individuals, it is necessary to use panel data in order to identify these macro effects. In this section we justify our estimation procedure on theoretical grounds. As a matter of fact, our justification is valid for the estimation of any dynamic conditional model on panel data when macro explanatory variables are possibly present.

Suppose that one has available a complete panel data on T equally spaced periods ($t=1,\dots,T$) for n individuals ($i=1,\dots,n$). Let Y_{it} be the endogenous random variable(s) observed at time t for the ith individual. Let X_{it} and Z_t be vectors of explanatory variables where X_{it} vary across individuals while Z_t do not. For instance, X_{it} may be *IR*1 or *MSD*, while Z_t may be *IGT* or *IGS*.

Let $Y_{i,s}^t$ be the set of variables $\{Y_{i,s}, Y_{i,s+1},\dots, Y_{i,t}\}$ where $s \leqq t$. We make the following assumptions:

Assumption A.1 (Markov Specification). For any $i=1,\dots,n$, and any $t=h+1,\dots,T$:

$$\Pr(Y_{it}|Y_{i,-\infty}^{t-1}, X_{i,-\infty}^{t}, Z_{-\infty}^{t}) = \Pr(Y_{it}|Y_{i,t-h}^{t-1}, X_{i,t-h}, Z_{t-h}^{t}).$$

where $\Pr(A|B)$ is the conditional density of the variables in A given the variables in B, and h is the maximum lag specified. It is assumed that $h<T$.

Given the choice of a family (in general parametric) of conditional distributions, Assumption A.1 is nothing else than the specification of a Markovian structure of order h.

Assumption A.2 (stability). (a) For any $i=1,\dots,n$, and any t, s in $\{h+1,\dots,T\}$:

$$\Pr(Y_{it}|Y_{i,t-h}^{t-1}, X_{i,t-h}^{t}, Z_{t-h}^{t}) = \Pr(Y_{is}|Y_{i,s-h}^{s-1}, X_{i,s-h}^{s}, Z_{s-h}^{s}),$$

(b) For any i, j in $\{1,\dots,n\}$, and any $t=h+1,\dots,T$:

$$\Pr(Y_{it}|Y_{i,t-h}^{t-1}, X_{i,t-h}^{t}, Z_{t-h}^{t}) = \Pr(Y_{jt}|Y_{j,t-h}^{t-1}, X_{j,t-h}^{t}, Z_{t-h}^{t}).$$

Assumptions A2(a) and A2(b) respectively require that the conditional model of interest be stable across time and across individuals. Clearly some stability assumptions, which may not be as strong, are needed in order to estimate a model.

The next assumption deals with the sampling of individuals.

Assumption A.3 (Sampling). The n stochastic vector processes $\{(Y_{it}, X_{it}); t=-\infty, T\}$ for $i=1,\dots,n$ are mutually independent given the stochastic process $\{Z_t; t=-\infty, T\}$, i.e. for any i:

$$(Y_{i,-\infty}^{T}, X_{i,-\infty}^{T}) \perp \{(Y_{j,-\infty}^{T}, X_{j,-\infty}^{T}); j \neq i\} | Z_{-\infty}^{T},$$

where $A \perp B|C$ denotes that A and B are conditionally independent given C.

For instance, if there are no macro variables Z_t, then Assumption A.3 simply means that the sampling of individuals is random.

Assumption A.4 (Exogeneity). For any $i=1,\dots,n$, and any $t=1,\dots,T$:

$$X_{i,t+1}^{+\infty}, Z_{t+1}^{+\infty} \perp Y_{i,-\infty}^{t} | X_{i,-\infty}^{t}, Z_{-\infty}^{t},$$

If there are no macro variables Z_t, then Assumption A.4 simply requires that Y_{it} does not Granger cause X_{it}, or equivalently that X_{it} is strictly exogeneous to Y_{it} (see Chamberlain (1982), Bouissou, Laffont, and Vuong (1985)).

Assumptions A.1 to A.4 can be considered as the standard assumptions underlying the estimation of a dynamic conditional model on panel data.[9] It is worth noting that we obtain as a special case ($h=0$, $T=1$) the assumptions that are implicit in the estimation of a conditional model on a cross section, and as another special case $(n=1)$ the assumptions that justify the estimation of a conditional model on time series.

We now consider the likelihood function associated with the observations on the panel $\{Y_{it}, X_{it}, Z_t;\ i=1,\dots,n,\ t=1,\dots,T\}$. Since h may not be null, we shall in fact consider the conditional likelihood function L_{YXZ} given all the variables prior to period $h+1$, i.e.

$$L_{YXZ} = \Pr\,[((Y^T_{i,h+1}, X^T_{i,h+1});\ i=1,\dots,n),\ Z^T_{h+1}|((Y^h_{i,-\infty}, X^h_{i,-\infty});\ i=1,\dots,n),\ Z^h_{-\infty}].$$

We have:

$$L_{YXZ} = L_{Y|XZ} \times L_{XZ}$$

with

$$L_{Y|XZ} = \Pr\,[(Y^T_{i,h+1};\ i=1,\dots,n)|((Y^h_{i,-\infty}, X^T_{i,-\infty});\ i=1,\dots,n),\ Z^T_{-\infty}] \tag{3}$$

$$L_{XZ} = \Pr\,[(X^T_{i,h+1};\ i=1,\dots,n),\ Z^T_{h+1}|((Y^h_{i,-\infty}, X^h_{i,-\infty});\ i=1,\dots,n),\ Z^h_{-\infty}] \tag{4}$$

Since L_{YXZ} is the (conditional) likelihood for $(((Y^T_{i,h+1}, X^T_{i,h+1});\ i=1,\dots,n),\ Z^T_{h+1})$ and since L_{XZ} is the (conditional) likelihood for $((X^T_{i,h+1};\ i=1,\dots,n),\ Z^T_{h+1})$, it follows that $L_{Y|XZ}$ as defined in (3) is the conditional likelihood for $(Y^T_{i,h+1};\ i=1,\dots,n)$ given $((X^T_{i,h+1};\ i=1,\dots,n),\ Z^T_{h+1})$.

We have:

$$\begin{aligned}
L_{Y|XZ} &= \prod_{t=h+1}^{T} \Pr\,[(Y_{i,t};\ i=1,\dots,n)|((Y^{t-1}_{i,-\infty}, X^T_{i,-\infty});\ i=1,\dots,n),\ Z^T_{-\infty}] \\
&= \prod_{i=1}^{n}\prod_{t=h+1}^{T} \Pr\,[Y_{it}|((Y^{t-1}_{j,-\infty}, X^T_{j,-\infty});\ j=1,\dots,n),\ Z^T_{-\infty}] \\
&= \prod_{i=1}^{n}\prod_{t=h+1}^{T} \Pr\,[Y_{it}|\,Y^{t-1}_{i,-\infty}, X^T_{i,-\infty}, Z^T_{-\infty}] \\
&= \prod_{i=1}^{n}\prod_{t=h+1}^{T} \Pr\,[Y_{it}|\,Y^{t-1}_{i,-\infty}, X^t_{i,-\infty}, Z^t_{-\infty}]
\end{aligned}$$

where the first equation is an identity, the second and third equations follow from Assumption A.3, and the fourth equation from Assumption A.4. Moreover, it follows from Assumption A.1 that:

$$L_{Y|XZ} = \prod_{i=1}^{n}\prod_{t=h+1}^{T} \Pr\,[Y_{it}|\,Y^{t-1}_{i,t-h}, X^t_{i,t-h}, Z^t_{t-h}]$$

and from Assumption A.2 that:

$$L_{Y|XZ} = \prod_{i=1}^{n}\prod_{t=h+1}^{T} \Pr\,[Y = y_{it}|\,Y^1_h = y^{t-1}_{i,t-h},\ X^0_h = x^t_{i,t-h},\ Z^0_h = z^t_{t-h}] \tag{5}$$

where y_{it}, $y^{t-1}_{i,t-h}$, $x^t_{i,t-h}$, z^t_{t-h} are the observed realizations of the random variables Y_{it}, $Y^{t-1}_{i,t-h}$, $X^t_{i,t-h}$, Z^t_{t-h}, and Y, Y^1_h, X^0_h, Z^0_j are the random variables implicitly defined by the stability Assumption A.2.

Each of our conditional logit models is estimated by maximizing a conditional likelihood function of the form (5) where the conditional probabilities are defined by equation (1) and the parameters are the α's and β's which satisfy the ANOVA constraints (2). From the general properties of conditional maximum likelihood estimation (see

Anderssen (1973), Vuong (1983)) it follows that this procedure leads to consistent estimates. It is also worth noting from Equation (5) that the conditional likelihood $L_{Y|XZ}$ is written as if all the observations were independent where one observation is an observation on a firm at a given period. In addition Equation (5) shows that we can pool all these $n(T-h)$ observations.

3. DISEQUILIBRIUM DYNAMICS

Our purpose is to explain using the variables that were mentioned in Section 1 the transition matrix associated with the four possible disequilibrium regimes (see Equation (1)). Specifically, we consider the transition probability from one state to another 3 months later. We have then considered only the dates for which a survey was available 3 months earlier. These dates are 7506, 7606, 7706, 7806, 7901, 7906, 8001, 8006, 8101, 8106, 8201, and 8206 (see Section 1). The number of observations in each sector, where an observation corresponds to a firm for a given date, is:

Sector 1: 1241 observations,
Sector 2: 4885 observations,
Sector 3: 2302 observations,
Sector 4: 449 observations,
Sector 5: 5293 observations.

The transition matrix for the whole industry has the form:

$$\begin{array}{cc} \begin{array}{cccc} KU & UC & CU & RI \end{array} & \\ \begin{bmatrix} p(1/1) & p(1/2) & p(1/3) & p(1/4) \\ p(2/1) & p(2/2) & p(2/3) & p(2/4) \\ p(3/1) & p(3/2) & p(3/3) & p(3/4) \\ p(4/1) & p(4/2) & p(4/3) & p(4/4) \end{bmatrix} & \begin{array}{c} KU \\ UC \\ CU \\ RI \end{array} \end{array}$$

where $p(j/k)$ denotes the transition probability from state k to state j. From the observations pooled over the 12 periods that were singled out above we can obtain the following observed three-month transition matrix for the whole industry with probabilities given as percentages:

$$\begin{bmatrix} 85{\cdot}82 & 24{\cdot}69 & 24.31 & 12{\cdot}13 \\ 7{\cdot}00 & 64{\cdot}24 & 2{\cdot}74 & 18{\cdot}53 \\ 5{\cdot}73 & 2{\cdot}32 & 65{\cdot}45 & 14{\cdot}51 \\ 1{\cdot}45 & 8{\cdot}74 & 7{\cdot}51 & 54{\cdot}84 \end{bmatrix}$$

There is for each regime a high probability of staying in the same regime. Moreover, the Keynesian unemployment regime appears to be an absorbing state. Similar characteristics are obtained when transition probabilities are computed for each sector. These qualitative features must, however, be treated with care since the transition probabilities are influenced by some macroeconomic variables that were not invariant over the period under study.

Table II presents a first set of estimation results that were obtained by using only the lagged regime indicator $IR1$ and the individual demand surprise indicator MSD.[10]

These results should be read as follows. When the upper tail probability (UTP) is larger than 5% it means that the current model cannot be rejected against the corresponding unconstrained (or saturated) model by a log-likelihood ratio test at the 5% significance level.[11] The number below an explanatory variable is the *UTP* in % of the chi-square Wald statistic that is used to test that the variable is significant. If this number is less than 5 it means that the suppression of the effect is rejected at the 5% significance level.[12] When an explanatory variable other than *IR*1 is significant at the 5% level we give for the first category of that variable ($IX = 1$) the signs of the effects on the four disequilibrium regimes.[13] For instance, (+, +, −, 0) means that an over evaluation in demand ($MSD = 1$) relatively increases the probabilities of being in regimes 1 and 2, decreases the probability of being in regime 3, and has no significant effect on the probability of being in regime 4 ceteris paribus.

TABLE II

Model IR/IR1, MSD

Sector \ *IR*	*IR*1	*MSD*	*UTP*
1	0%	18% (+, 0, 0, 0)	10·70%
2	0%	0% (+, +, −, −)	5·53%
3	0%	0% (+, +, −, −)	87·80%
4	0%	44·8% (0, 0, 0, 0)	29·80%
5	0%	0% (+, +, −, −)	24·00%

As expected from the observed transition matrices given above, we find that the lagged regime indicator *IR*1 is strongly significant for every sector. We also observe that the demand surprise indicator is strongly significant for sectors 2, 3, and 5, while it is not for sectors 1 and 4. Sector 1 (Agricultural and Food Industries) always gave poor results and we shall abstain from giving any explanation. On the other hand, the non-significance of the demand surprise indicator in sector 4 (Automobile and Transportation) is probably due to the predominance of production to orders in this sector. Finally, when the demand surprise indicator is significant it has the "correct" signs. By "correct" signs we mean that when a firm has over-evaluated its future demand, this increases its probability of being in the excess supply (of good) regimes ($IR = 1$, $IR = 2$) and decreases its probability of being in the excess demand (of good) regimes ($IR = 3$, $IR = 4$).

For our second set of results, we introduce the macroeconomic variables that are suggested by the disequilibrium microeconomic literature and described in Section 1. We only give the main results for each sector.

SECTOR 2

Intermediate goods

IR	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGS* 81%	*ISB* 0% (−, 0, 0, +)			$UTP = 6{\cdot}43\%$
IR	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGS* 57%	*IGS*1 0% (+, 0, 0, −)	*IGS*2 0% (−, 0, 0, +)	*IGS*3 10%	$UTP = 5{\cdot}45\%$
IR	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGT* 25%	*IGT*1 5·46% (0, −, 0, 0)	*IGT*2 1·31% (−, 0, +, 0)	*IGT*3 15%	$UTP = 21{\cdot}20\%$

In this sector a stimulus on total public expenditures has after 6 months (*IGT*2) the expected effect of decreasing the probability of being in the Keynesian unemployment regime. Sectoral public expenditures do not have, however, a clear effect. A possible explanation is the following: In the short run public expenditures have no effect (*IGS*); since public expenditures are increased during Keynesian unemployment periods, we observe an unexpected negative effect (*IGS*1); finally an effect in the expected direction emerges after 6 months (*IGS*2). The sectoral cost of labour indicator (*ISB*) has significant effects and behaves as an indicator of purchasing power since a stimulus leads to a decrease in the probability of being in the Keynesian unemployment regime and to a simultaneous increase in the probability of being in the repressed inflation regime. This latter remark actually holds for all sectors.

SECTOR 3

Professional equipment

IR	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGS*3 14%	*ISB* 0% (−, 0, 0, +)			*UTP* = 92·7%
IR	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGS*1 25%	*IGS*2 10%	*IGS*3 3·79% (−, 0, 0, 0)	*ISB* 0% (−, 0, 0, +)	*UTP* = 76·8%

When sectoral public expenditures have significant effects (in general after 9 months: *IGS*3) they have the expected signs since a stimulus on public expenditures decreases the probability of being in the Keynesian unemployment regime.

SECTOR 4

Automobile and transportation

IR	*IR*1 0%	*IGS*1 0·72% (−, 0, 0, 0)	*IGT*2 0% (−, 0, 0, 0)	*ISN* 0% (−, 0, 0, 0)			*UTP* = 39·3%
IR	*IR*1 0%	*IGS*1 4·97% (0, 0, 0, −)	*IGT*2 0·51% (−, 0, 0, 0)	*ISB* 0·94% (−, 0, 0, +)	*ISB*1 6·5%	*ISN* 0.05% (−, 0, 0, 0)	*UTP* = 35·7%

Sectoral and total public expenditures (*IGS* and *IGT*) are often significant with the correct signs. The indicator of purchasing power *ISN* plays the expected role since a stimulus on *ISN* decreases the probability of being in the Keynesian unemployment regime.

SECTOR 5

Consumption goods

*IR*1	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGT*3 0·03% (−, −, 0, +)	*ISN* 0% (−, 0, 0, +)			*UTP* = 17%
*IR*1	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGS*2 0% (−, 0, −, +)	*IGS*3 0·04% (+, 0, +, −)	*IGT*2 39%	*IGT*3 1·87% (−, −, 0, 0)	*UTP* = 27·6%
IR	*IR*1 0%	*MSD* 0% (+, +, −, −)	*IGS*1 10%	*IGS*2 2·31% (0, 0, 0, +)	*IGS*3 0% (+, 0, 0, −)	*ISB* 48%	*UTP* = 56·7%

In this sector total public expenditures after 9 months ($IGT3$) and sectoral public expenditures after 6 months ($IGS2$) have significant effects with the correct signs. Sectoral public expenditures after 9 months ($IGS3$) have significant effects but with the incorrect signs. The indicator of purchasing power ISN is strongly significant with the expected signs, while the sectoral real cost of labor indicator ISB is not significant.

5. CONCLUSION

This preliminary study has yielded the following results. First, the stability of the results with respect to the various sectors is striking. In all sectors we found that demand surprises are very significant in explaining the disequilibrium regimes with always the expected signs. The fact that an increase in public expenditures tends to decrease the probability of being in the Keynesian unemployment regime was clearly shown with a lag of 6 to 9 months. This result does not have, however, the stability of the previous ones. Our difficulties in obtaining clear estimated effects of public expenditures may be due to the endogeneity of this variable.

The index of purchasing power when significant has the right sign in the sense that an increase in this variable tends to decrease the probability of being in the Keynesian unemployment regime. We were, however, unable to exhibit the positive impact of an increase in the sectoral wage level on the probability of being in the classical unemployment regime. When this variable is significant it plays the same role as a purchasing power variable.

Finally, we must note that our analysis is hindered by the predominance of the Keynesian unemployment regime. Our inability to find evidence of the effect of sectoral real wages on the probability of being in the classical unemployment regime may be due to this characteristic of our sample.

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NOTES

1. The possibility of using such surveys for analyzing disequilibria was also suggested by Malinvaud (1981) and Kooiman (1982).
2. For more details on these surveys, see e.g. Bouissou, Laffont, and Vuong (1984).
3. The role of this variable has been emphasized in a macro-disequilibrium framework by Green and Laffont (1981) and in a microeconomic model by Bouissou, Laffont, and Vuong (1984).
4. The same variable was used by Konig, Nerlove, and Oudiz (1981).
5. Two more complex methods of constructing the indicators IQ and IL from the *INSEE* surveys were tried. For more details, see Bouissou, Laffont, and Vuong (1984).
6. The other result obtained by these authors is a great jump in Keynesian unemployment at the end of 74, i.e. just following the first oil crisis. Though this second result cannot be observed with the present method of constructing IR due to missing data, it can however be observed with the second method of constructing IR that was studied in Bouissou, Laffont, and Vuong (1984).
7. For more details on how these indicators as well as their latent continuous variables were constructed from the series available in the Comptes Nationaux Trimestriels, see Bouissou, Laffont, and Vuong (1984).
8. Alternatively, using the ANOVA constraints (2), it follows that $\mu = (1/KR)\sum_{k=1}^{KR} \log \Pr(IR_{it} = k | IR1_{it}, IA_{it}, IB_{it}, \ldots)$. Thus equation (1) can be thought of as defining the conditional probabilities in terms of deviations from their log-mean.
9. Any of these assumptions can actually be tested. For instance, Bouissou, Laffont, and Vuong (1985) have derived some readily applicable tests of Assumption A.4 when there are no macro variables Z_t.

10. All our empirical results were obtained by using the program CALM written by J. P. Link. This program estimates conditional ANOVA log-linear probability models (for the theory, see Nerlove and Press (1976), Ottenwaelter and Vuong (1981), Vuong (1982), and for a survey Nerlove (1983)).

11. This test can be thought of as a specification test for the model defined by equation (1). Specifically, it tests whether restricting effects to bivariate interactions is supported by the data. For formulas giving the appropriate degrees of freedom of the chi-square statistics, see Haberman (1974) and Vuong (1982).

12. In the tables below, if the upper-tail probability is less than 0·005%, it appears as a zero.

13. As mentioned in Section 2, the ANOVA parameterization is used. Since IR has 4 categories, it follows that the (bivariate) effect of an explanatory variable with J categories is characterized by $4\times J$ ANOVA parameters of which $3\times(J-1)$ are independent due to the usual ANOVA constraints. Hence, when $J=2$ it suffices to give the signs of the ANOVA parameters associated with the first category of the dichtomous variable.

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